Article Type: Response to Editor

Resilience and the reliability of spectral entropy to assess ecosystem stability

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Running head: Vegetation resilience

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Keywords: Vegetation, Resilience, Stationarity, Entropy, NDVI, Stability

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Main body

Zurlini et al. (2014) formulated interesting thoughts on our recent publication dealing with the assessment of ecosystem stability using remote sensing time series (De Keersmaecker et al., 2014). Their main concerns can be summarised as follows: (i) the normalized spectral entropy (H_{Sn}; Zaccarelli et al., 2013) that was used to quantify resilience, should be interpreted as a metric for structural irregularity, rather than regularity, and (ii) our focus was on local stability and the ability to return to a stable point or trajectory only (i.e. engineering resilience), whereas stability metrics are commonly used to assess the adaptive capacity to remain within the same stability domain (i.e. ecological resilience) (Dakos et al., 2012; Holling, 1996; Pimm, 1984).

First, since we applied H_{Sn} to anomaly time series instead of to original Normalised DifferenceVegetation Index (NDVI) time series, the interpretation of the H_{Sn} metric also changes from structural irregularity to regularity. For example, when a large disturbance results in vegetation response persistent anomalies, the time series regularity would decrease (i.e. increase in H_{Sn}) but also the irregularity of the anomaly time series would decrease (i.e. decrease in H_{Sn}).

Although we believe that both interpretations of H_{Sn} are valid, we based our analysis on the anomaly time series as it avoids the sensitivity of H_{Sn} to shape effects. Shape effects can have strong impact on the interpretation of H_{Sn} as a regularity metric as is illustrated in Fig. 1. Both time series shown are equally regular, but have different H_{Sn} values, which complicates the interpretation of regularity, whereas this is not the case for the anomaly time series with equal H_{Sn} values.

Second, we agree that De Keersmaecker et al. (2014) focuses on local stability, whereas other stability measures can be important as well (Holling, 1996). However, these other stability measures are difficult to quantify based on metrics that assume stationarity and consequently do not account for multiple stable states (e.g. H_{Sn} is based on a Fourier transformation which assumes stationarity (Zaccarelli et al., 2013)). For example, it is difficult to interpret H_{Sn} as an indicator of ecological resilience without knowing when the time series switches from one local stability regime to another. This is illustrated in Fig. 2, which shows two time series with similar H_{Sn} values but different stability regimes (i.e. time series A flips between two regimes, whereas time series B has only one regime). Therefore, we believe that detecting tipping points is imperative before assessing other stability measures. The interpretation of the stability metrics described in De Keersmaecker et al. (2014) is therefore only useful within a regime of local stability.

Finally, we want to stress that the conclusion of De Keersmaecker et al. (2014) was exactly that understanding the reliability of stability metrics is essential when assessing ecosystem stability. This is especially true because time series properties (e.g. the presence of multiple stable states and the use of original vs. anomaly time series, as demonstrated here) can highly affect the interpretation of these metrics.

References

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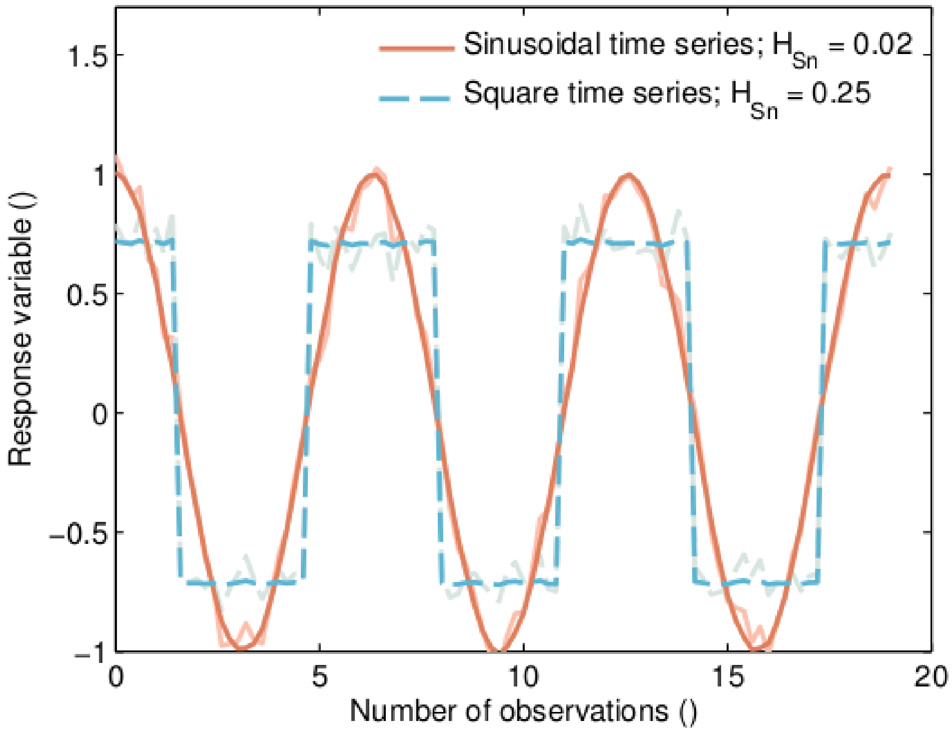
Tables

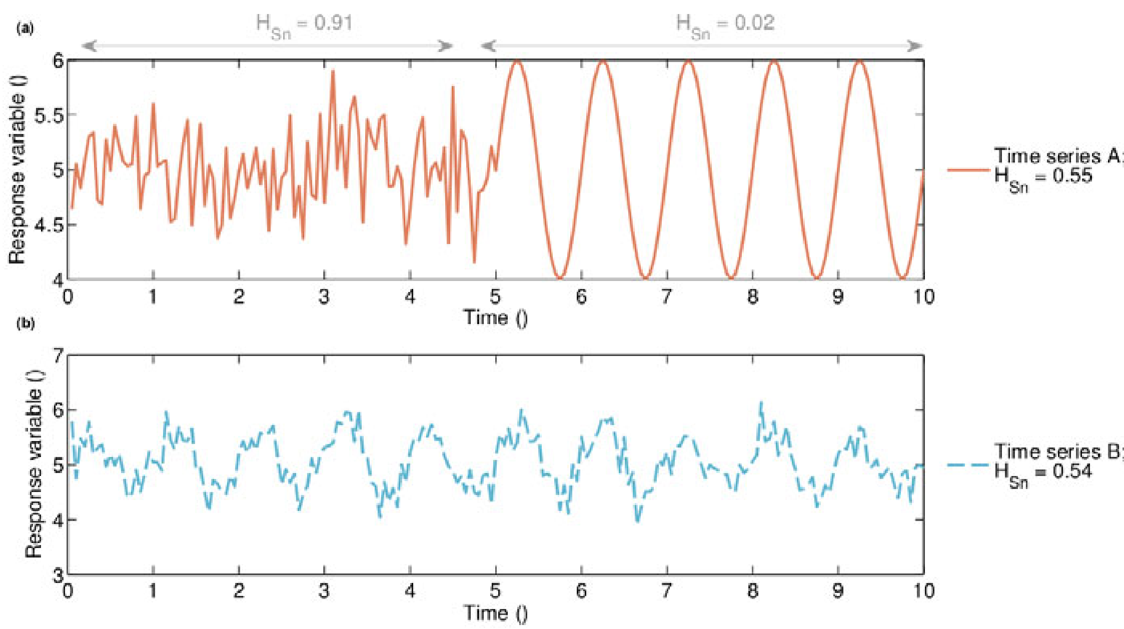
Figure legends

Figure 1: Effect of the seasonality shape on the H_{Sn} metric. Time series 1 and 2 have the same standard deviation and both show a strong regularity. As the H_{Sn} value of the square time series equals 0.25, while the H_{Sn} value of the sinusoidal time series equals 0.02, the H_{Sn} metric is not only sensitive to structural regularity of the time series, but also to the seasonal shape of the time series. After adding noise to the time series (semi-transparent lines), the H_{Sn} of the square and sinusoidal time series equals respectively 0.30 and 0.03 respectively, while their anomaly time series have a H_{Sn} value of 0.87.

Figure 2: Effect of non-stationarity on the H_{Sn} metric. Time series A has two regimes with a clear break point: the first part of the time series follows a white noise pattern ($H_{Sn} \approx 0.91$), while the second part shows a sinusoidal pattern ($H_{Sn} \approx 0.02$). The total time series has a H_{Sn} metric of 0.55. Time series B has one regime which is a combination of a white noise pattern and a sinusoidal time series, but its H_{Sn} is similar to the H_{Sn} of time series A. This illustrates the importance of break point detection for interpreting the H_{Sn} metric on non-stationary time series.



Sinusoidal time series; H_{Sn} = 0.02
Square time series; H_{Sn} = 0.25
Response variable ()
Number of observations ()
1.5
1
0.5
0
−0.5
−1
0
5
10
15
20



(a)
H_{Sn} = 0.91
H_{Sn} = 0.02
Response variable ()
Time ()
Time series A; H_{Sn} = 0.55
(b)
Response variable ()
Time ()
Time series B; H_{Sn} = 0.54